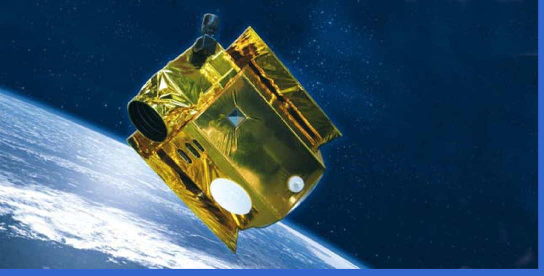

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"RECENT ADVANCES IN QUANTITATIVE REMOTE SENSING"

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A MULTISTAGE CHANGE DETECTION METHODOLOGY APPLYING STATISTICAL MULTISOURCE ANALYSIS.

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1. ABSTRACT

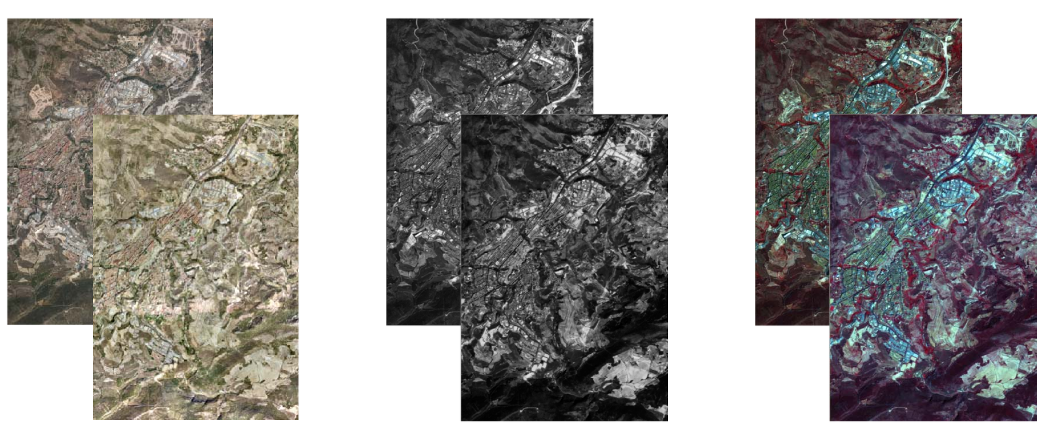
Assessment and detection of environmental changes is one the most frequent applications in remote sensing. As a result, there has been a great proliferation of research on this particular topic, leading to different methodologies for detecting changes (Radke 2005, Foody 2009, Kennedy 2009) from data supplied by multi-temporal images acquired from spaceborne sensors. The basic objective in a change detection process is to detect groups of pixels that are "significantly different" within a set of registered images of the same geographic area.

Moreover it must be taken into account that in the recent decades, advances in space technologies made possible to collect a large amount of information about the Earth Surface and its environment. Since these data have been acquired from multiple sources, their quantitative exploitation requires optimal strategies to benefit from their interactions, so that information of high quality and great applicability for the proposed objectives can be extracted. (Petit 2001).

2. INTRODUCTION

Actually, updating spatial databases for Land-Information systems (LIS) can be carried out by means of Change Detection (CD) procedures. These methodologies are referred to as supervised or unsupervised. Moreover, change detection approaches usually deal with one level resolution datasets, from which spectral and spatial features can be derived in order to analyze individually the corresponding difference images. In the supervised case, some well known methods and algorithms allow to perform a data fusion process of spectral and spatial data, so that a change detection label map is finally obtained. These processes have been proved efficient only in specific urban areas, where spatial data sets of similar resolutions are used. Unsupervised change detection techniques are less time consuming but more rigid in the sense that only one different image can be taken into account during the CD process. In this work, a multistage methodology is undertaken, so that several spectral and spatial features are derived at each resolution level from its respective data sources, and are further on integrated in a 'Statistical Multisource Analysis' in order to derive a change detection map. Digital Surface Models (DSM) are also used in order to optimize the reached results at the higher resolution level.

3. STUDY AREA AND AVAILABLE DATA



AERIAL IMAGES

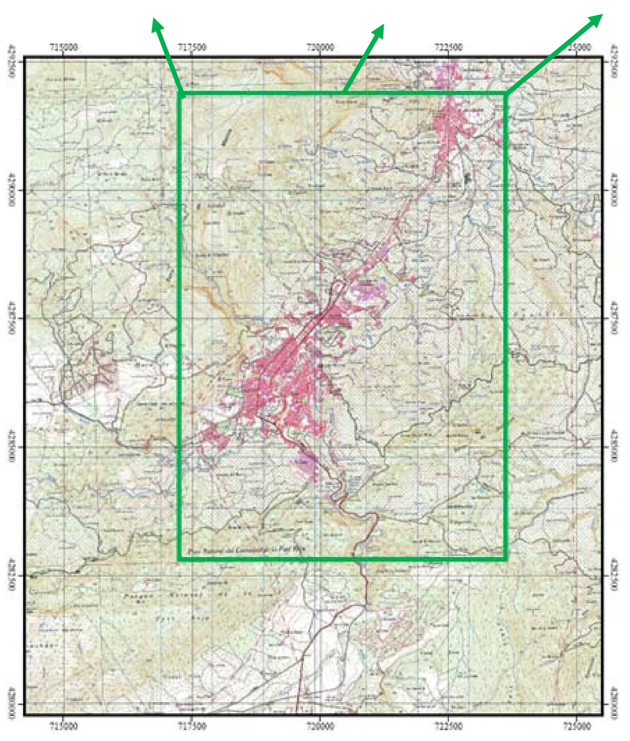
- **Images capture Dates:** 2005, 2007
- **Spatial Resolution:** 1m.
- **Spectral Resolution:** 0.445-0.698 μm
- **Image Bands:** R, G, B

SPOT5 PAN

- **Image capture Date:** 2005, 2008
- **Spatial Resolution:** 2.5m.
- **Spectral Resolution:** 0.70-0.90 μm
- **Image Band:** PANCHROMATIC

SPOT5 -XS

- **Image capture Date:** 2005, 2008
- **Spatial Resolution:** 10m.
- **Spectral Resolution:** 0.50-1.75 μm
- **Image Bands:** SWIR, NIR, R, G



AREA INFORMATION

- **Study area:** Alcoy (Valencia).
- **Surface:** 4460m x 6600m.
- **Surface type**: rural and urban.
- **Change Types:** buildings, roads and vegetation changes.

AREA FRAME

Lat: 38° 43' 38,68" N

Long: 0° 29' 21,49" W

Lat: 38° 40' 05,78" N

Long: 0° 26' 25,14" W

Figure 1. Study area and data sets

4. CHANGE DETECTION USING DSM's

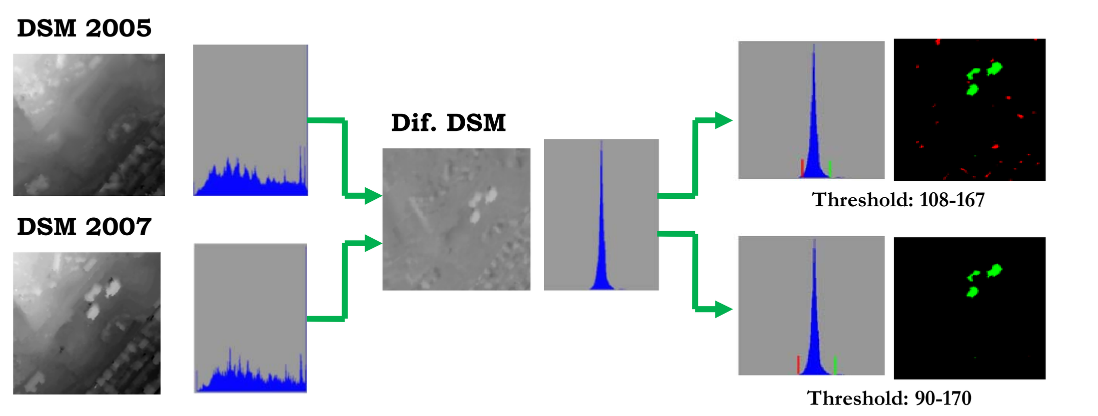


Figure 2. Difference DSM and thresholding process.

5. METHODOLOGICAL ASPECTS

The different phases of the proposed methodology are based in the following key features:

1. **MULTIRESOLUTION ANALYSIS**. This methodology aims to test Change Detection methods at different levels of resolution. In this study the following levels have been taken into account:

- **Level 1:** low spatial resolution satellite images (10 m).
- **Level 2:** high spatial resolution satellite images (2.5 m).
- **Level 3:** Aerial imagery and LIDAR data (1 m).

2. **MULTISOURCE ANALYSIS**. For a given resolution level, different Change Indices can derived, and then integrated in order to optimize the information on changes that have occurred into a specific area.

3. **IMAGE THRESHOLDING TECHNIQUES.** Techniques and algorithms based on image entropy have been tested, so that each Change Index can be binarized (i.e. change and no change). The threshold is obtained by an iterative process of the entropy function for the background and foreground values of the Change Index.

$$H_f(T) = -\sum_{g=0}^{T} p_f(g).\log p_f(g) \quad H_b(T) = -\sum_{g=T+1}^{G} p_b(g).\log p_b(g)$$

4. **CD FUSION APPROACH.** In this study several algorithms for integrating multisource data into a CD process have been considered. Currently, this operation is carried out by means of a data fusion procedure based on a Bayesian Probabilistic Model, so that each source of information can be properly weighted according to the following expression.

$$\sum_{1}^{Q} \lambda_k P_k(\omega_n) p\left(x_k^{ij}/\omega_n\right) \underset{\omega_n}{\overset{\omega_c}{\lessgtr}} \sum_{1}^{Q} \lambda_k P_k(\omega_c) p\left(x_k^{ij}/\omega_c\right)$$

Other multisource fusion algorithms, are based on fuzzy logic methods or on Dempster-Shaffer evidential theory.

5.1. WORK FLOW FOR MULTIRESOLUTION AND MULTISOURCE PROCESS

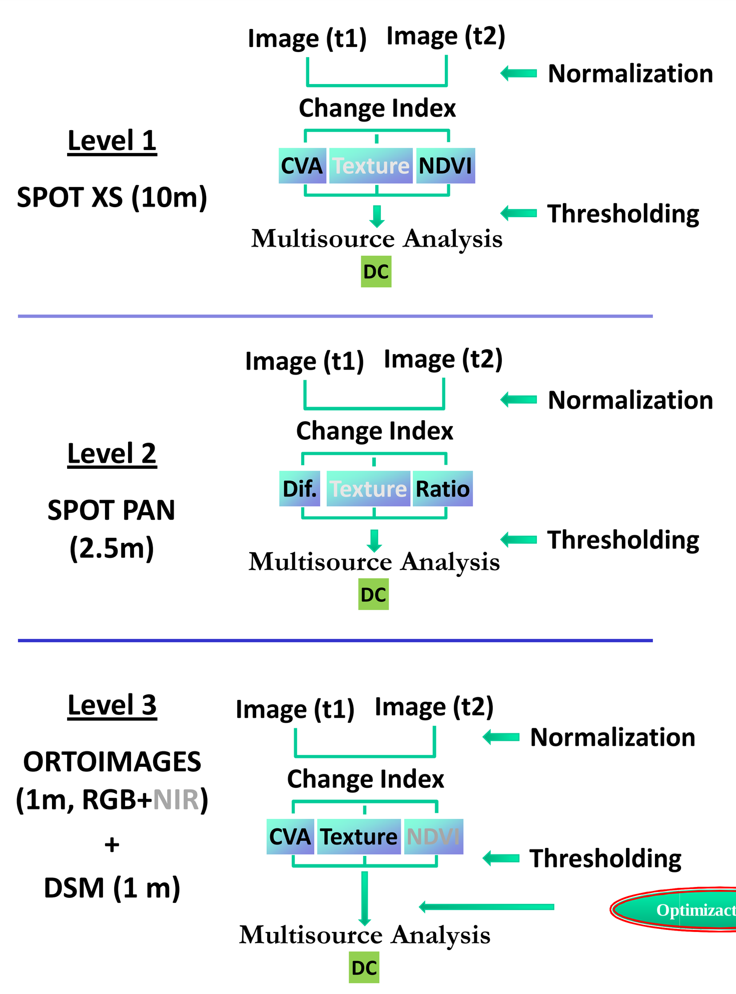


Figure 3. Flowchart for the proposed Change Detection methodology

Change Indices (CI) resulting from image algebra processes, can be obtained by 'Simple Difference', 'Ratio' or 'Change Vector Analysis' (CVA) operations, applied to the original data sets. The choice of the most appropriate method is given by the spectral and spatial resolutions of the considered sensor. Other indices can be also derived using textural measures and vegetation indices (NDVI). At Level 3, a 3D layer (DSM. Dif.) has also been introduced in the CD process.

5.2. RADIOMETRIC NORMALIZATION

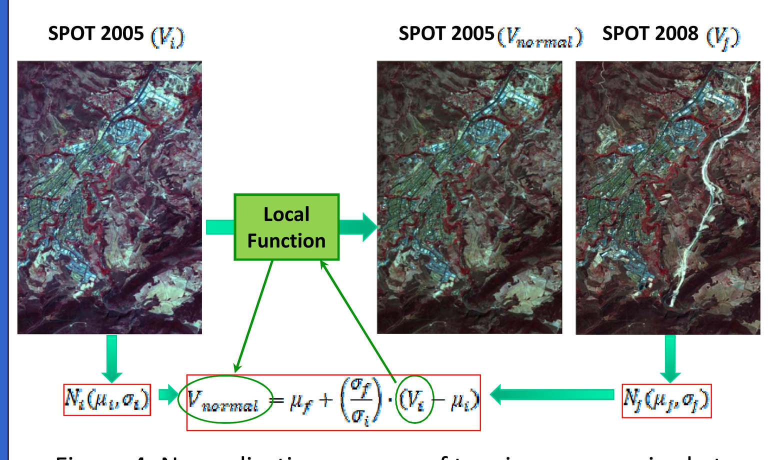


Figure 4. Normalization process of two images acquired at different dates.

Different tests have shown the need to normalize images radiometrically. This process compensates weather and lighting conditions when images are acquired at different positions or dates. This normalization process is based on global statistical parameters, so that they define the best normal distribution that fits on the histogram of each image. Then, a local function is applied to each image band separately.

5.3. TEXTURAL MEASURES

CO-OCCURRENCE MATRICES

Textural measures describe the gray level distribution on the neighborhood of each pixel by means of statistical variables such as variability, contrast, homogeneity, etc.

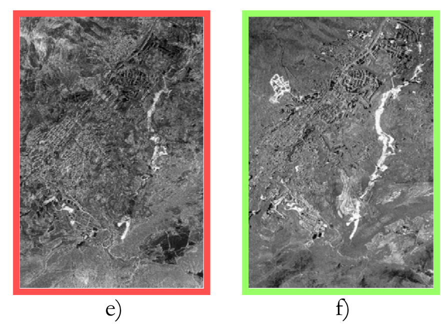


Figure 5. a) First image, b) Homogeneity, c) Second Moment, d) Dissimilarity, e) CVA (First image), f) CVA (Homogeneity).

6. RESULTS

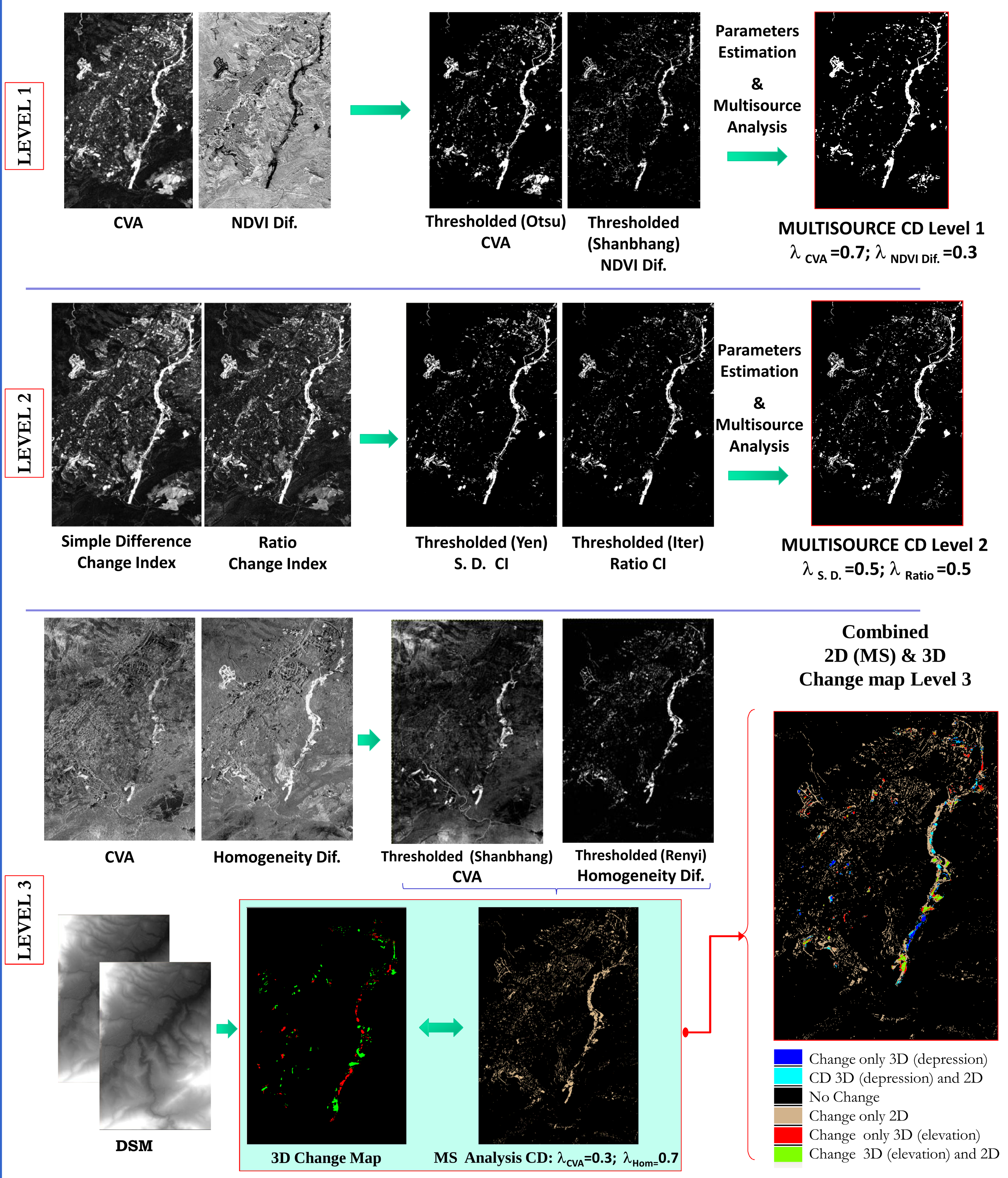
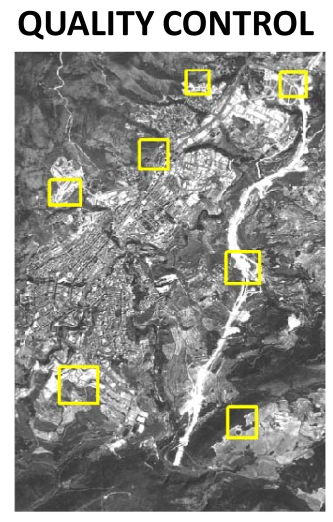


Figure 6. Change Indices, thresholded images, Multisource CD (Change Detecction processes for each resolution level).

THRESHOLDING AND STATISTICAL PARAMETERS FOR THE DIFFERENT CHANGE INDICES

	INDEX	THRESHOLDING	CLASS	STATISTICAL PARAMETERS μ	σ
LEVEL 1	CVA	Algorithm: **Otsu**	C	67,473	29,386
		Tr. Value: 38	NC	9,815	8,025
	NDVI	Algorithm: **Shanbhang**	C	76,714	21,698
		Tr. Value: 55	NC	15,981	12,003
LEVEL 2	DIF.F	Algorithm: **Yen**	C	86,529	26,344
		Tr. Value: 55	NC	8,835	10,402
	RATIO	Algorithm: **Iter**	C	50,503	13,542
		Tr. Value: 36	NC	4,142	4,768
LEVEL 3	CVA	Algorithm: **Shanbhang**	C	105,785	30,998
		Tr. Value: 71	NC	29,163	18,429
	TEXTURE HOMOGENEITY	Algorithm: **Renyi**	C	143,979	31,489
		Tr. Value: 105	NC	27,25	20,884
	DIFF. DSM	Manual	C	132,53	20,054
		Tr. Value: 115	NC	105,79	2,432

QUALITY CONTROL



Level 1

	Ground Truth (%)		Completeness	Correctness
Class	C	NC	96%	0.99%
C	96.3	0.5		
NC	3.7	99.5		
Total	100.0	100.0		

Level 2

	Ground Truth (%)		Completeness	Correctness
Class	C	NC	88%	99%
C	88.3	0.5		
NC	11.7	99.5		
Total	100.0	100.0		

Level 3

	Ground Truth (%)		Completeness	Correctness
Class	C	NC	91%	98%
C	91.4	1.8		
NC	8.6	98.2		
Total	100.0	100.0		

☞ These evaluation results are approximated since no reference change map is currently available for this purpose

7. CONCLUSIONS

In this work an unsupervised and multisource Change Detection (CD) methodology has been carried out. For this purpose, at different resolution levels several change indices have been derived from different sensors. Then, one of the main goals of this study was to apply image thresholding techniques in order to establish for each index, changed and unchanged areas, from where parameters estimates for these classes can be drawn. This has been accomplished means of thresholding methods based on entropy. It has been proven that some of these algorithms perform correctly for a given index at a certain resolution level. These results demonstrate that this phase in a CD process can be fully automated by means of this family of algorithms. Therefore, once the parameters for the probability density functions corresponding to change and unchanged values of a particular index are known, these can be used into a probabilistic multisource CD procedure that integrates all the derived indices for a given resolution level. It has also been verified that 3D data is a valuable source of information for a CD process where high resolution imagery is involved, since height changes can also be integrated into a final CD map. This methodology is now being applied with fuzzy logic procedures in order to evaluate the fusion process of the multisource datasets. The first results verify also the validity of these thresholding techniques for establishing the different membership functions. Future work will be undertaken using evidential approaches for multisource data analysis.

8. SELECTED REFERENCES

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